Towards Explainable NLP: A Generative Explanation Framework for Text Classification

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Presented by:
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Explainability Methods for NNs
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Overview

- Motivation
- Proposed solution
- Generative Explanation Framework (GEF)
    - Intuition
    - Base Classifier and Generator
    - Explanation Factor
    - Minimum Risk Training
- Experiment results

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Motivation

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But they are blackboxes for human beings!

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    - Review: "The phone feels sturdy, looks premium, and works great. For a mostly business user like me, these features, plus all the little software enhancements and customizations that I am allowed to do make it a very attractive device......."

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  - Attribute scoring:

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  - Attribute scoring:

Price	Packaging	Quality
4	5	5

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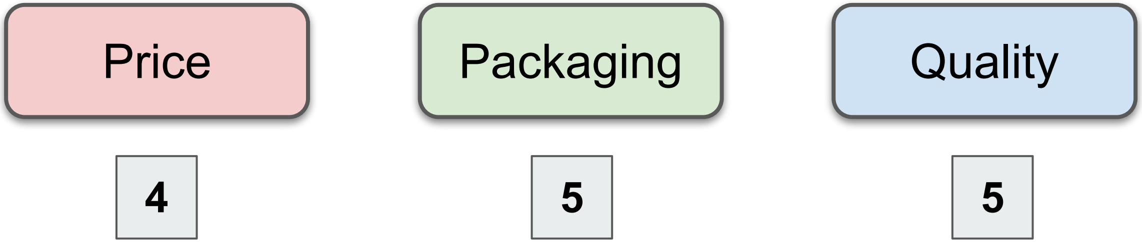

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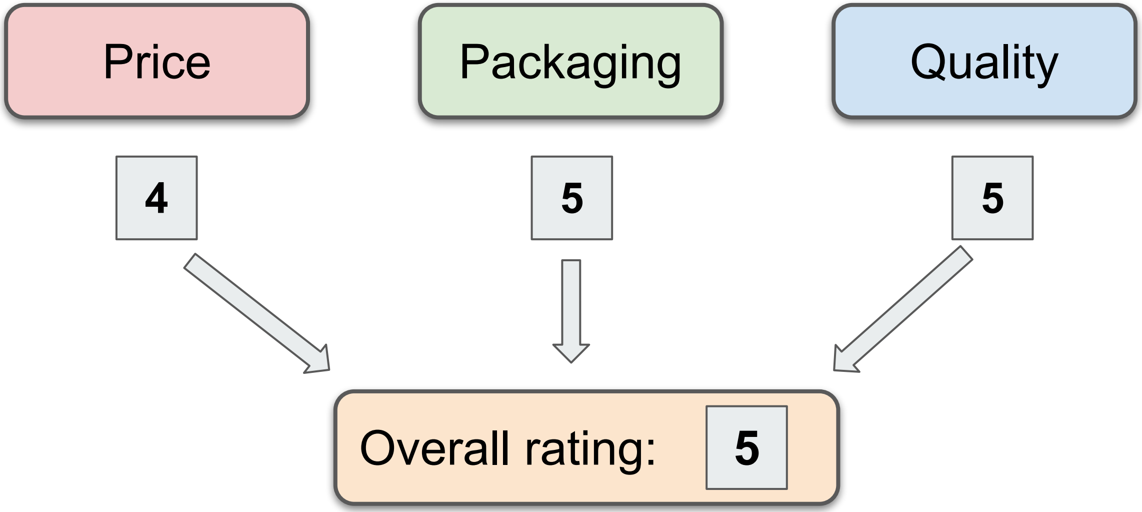

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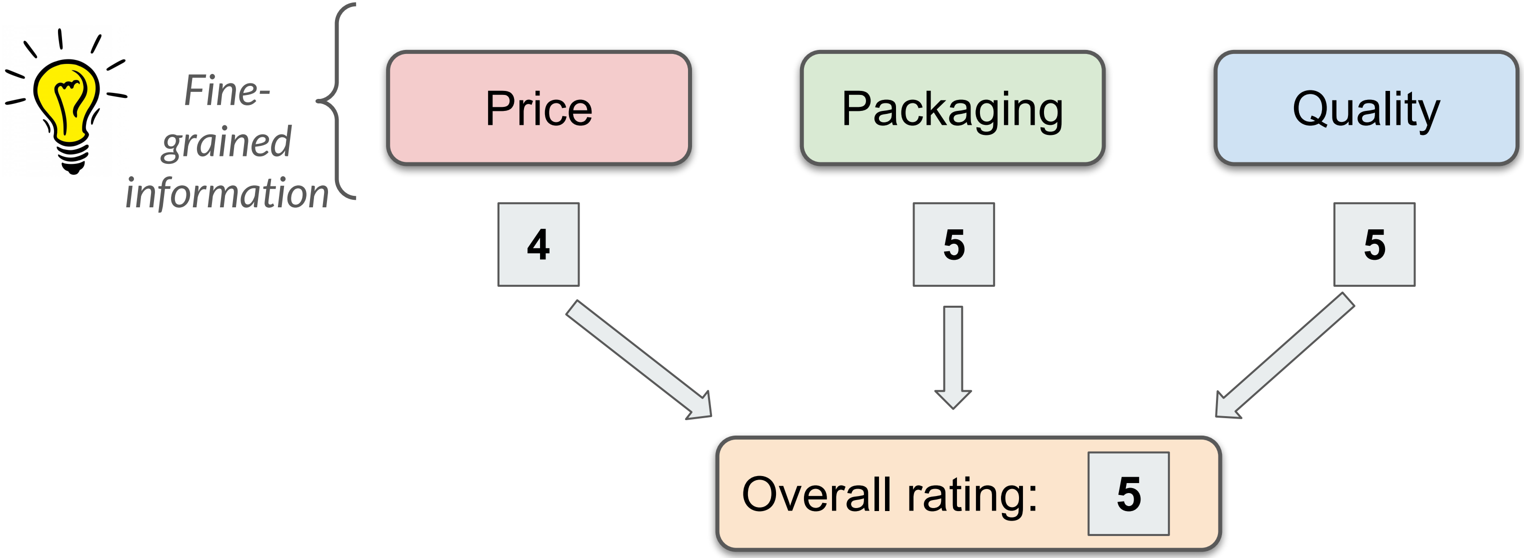

Motivation

- Deep learning methods have produced state-of-the-art results in many NLP tasks

Ability to explain rationale is essential for an NLP system!

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Proposed solution

- **Goal:**

  To build trustworthy **explainable** text classification **model** capable of explicitly **generating fine-grained information** for explaining their predictions

Proposed solution

- Generative Explanation Framework (**GEF**)
  - Makes classification decisions
  - Generates fine-grained explanations

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Generative Explanation Framework

Intuition - GEF

- Build a classifier model to do text classification

Generative Explanation Framework

Intuition - GEF

- Build a classifier model to do text classification
- Obtain good fine-grained information from raw text to explain the prediction (and improve performance?)

Generative Explanation Framework

Intuition - GEF

- **Q:** What is a fine-grained explanation?

Generative Explanation Framework

Intuition - GEF

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Generative Explanation Framework

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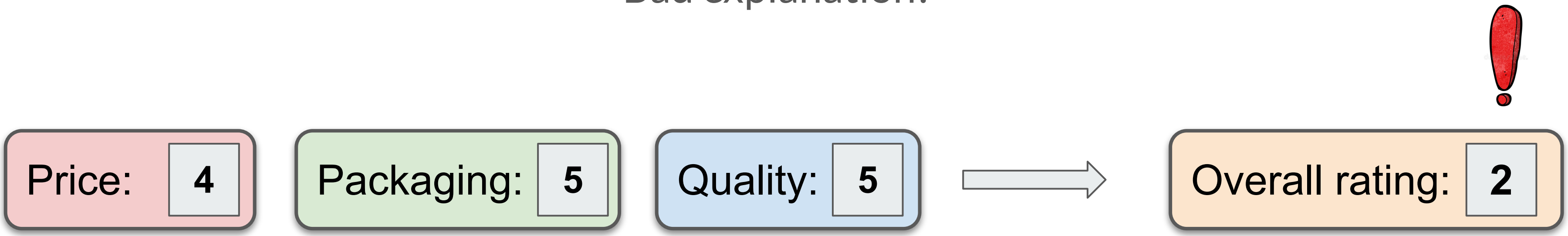
- Q: What is a **good** fine-grained explanation?

Generative Explanation Framework

Intuition - GEF

- **Q:** What is a **good** fine-grained explanation?

Bad explanation!

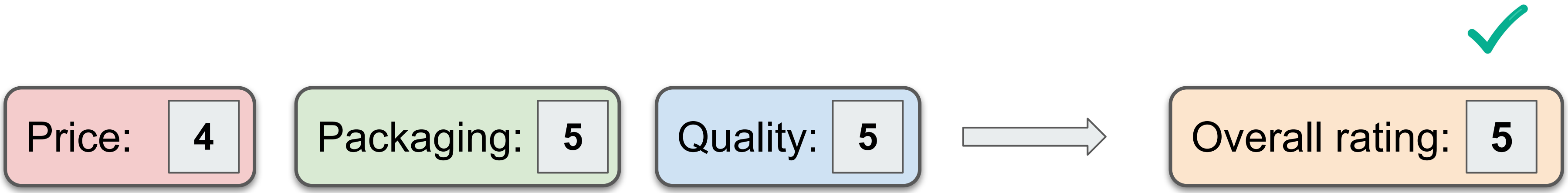


Generative Explanation Framework

Intuition - GEF

- **Q:** What is a **good** fine-grained explanation?

Good explanation!



Generative Explanation Framework

Data

- **Example:** Rating a product
  - Review text: “The phone feels sturdy, looks premium,.......”
  - Fine-grained/Golden explanations:

    Price: 4 | Packaging: 5 | Quality: 5

  - Output:

    Overall rating: 5

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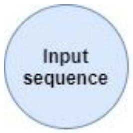
Generative Explanation Framework

Base Classifier and Generator

- Base classifier
    - Encoder-Predictor architecture



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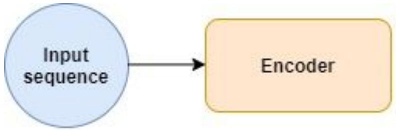

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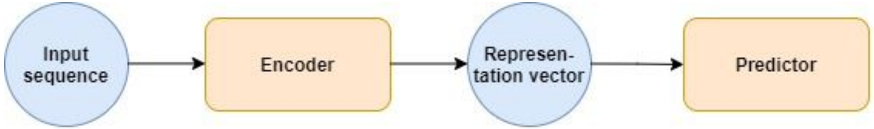

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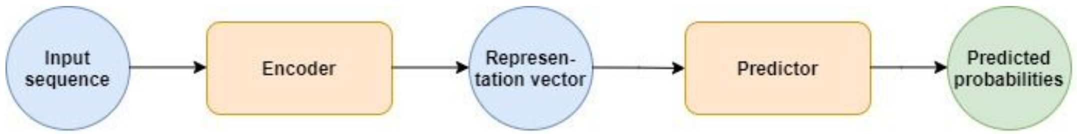

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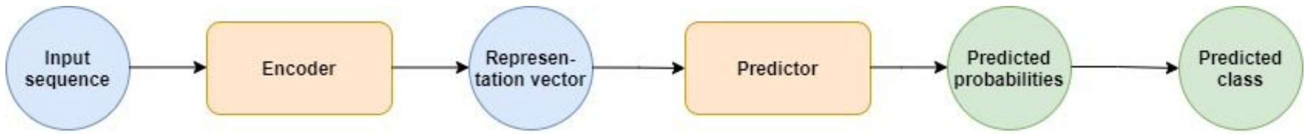

Generative Explanation Framework

Base Classifier and Generator

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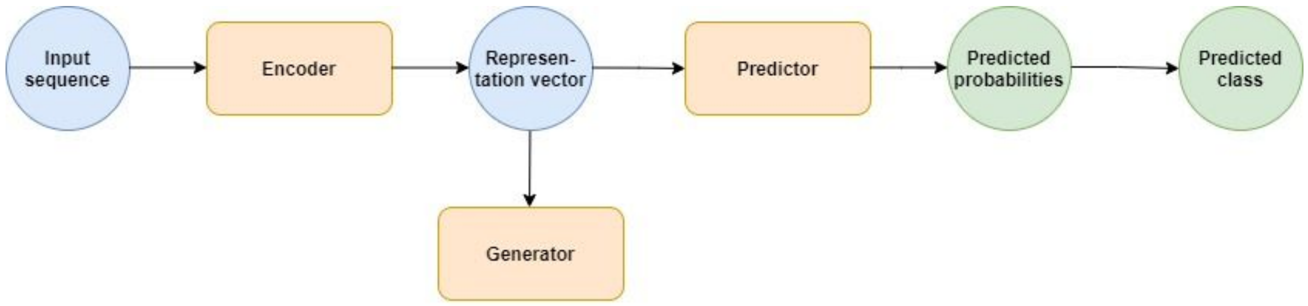

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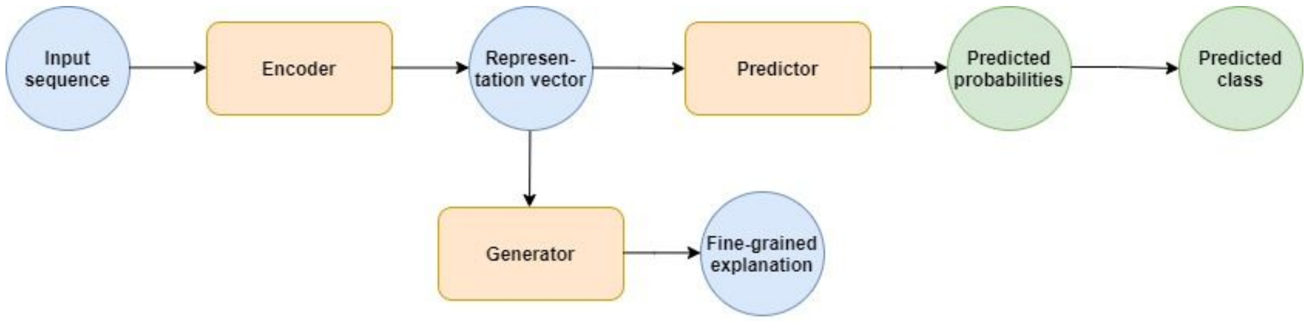


Generative Explanation Framework

Notations

Input sequence of texts: $S\{s_1, s_2, \ldots, s_{|S|}\}$

Output category: $y_i (i \in [1, 2, \ldots, N])$

Generative Explanation Framework

Algorithm so far...

- **Step -1:** Encode the input sequences to get representation vectors

$$v_e = Encoder([s_1, s_2, \cdots, s_{|S|}])$$

Generative Explanation Framework

Algorithm so far...

- **Step -1:** Encode the input sequences to get representation vectors

$$v_e = Encoder([s_1, s_2, \cdots, s_{|S|}])$$

- **Step -2:** A predictor takes those vectors as input and outputs probabilities by using softmax

$$P_{pred} = Predictor(v_e)$$

$$y = \arg\max_i (P_{pred,i})$$

Generative Explanation Framework

Algorithm so far...

- **Step -3:** Feed the representation vectors to a Generator G to generate fine-grained explanations

$$e_c = f_G(W_G \cdot v_e + b_G)$$

Generative Explanation Framework

Algorithm so far...

- **Step -3:** Feed the representation vectors to a Generator G to generate fine-grained explanations

$$e_c = f_G(W_G \cdot v_e + b_G)$$

- **Loss:**

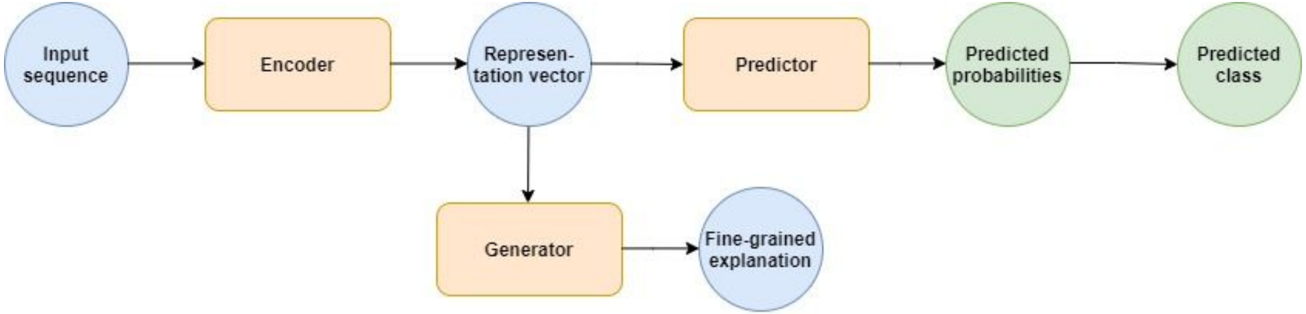
  Overall loss = Classification loss + Explanation generation loss

$$\mathcal{L}(e_g, S, \theta) = \mathcal{L}_p + \mathcal{L}_e$$

Generative Explanation Framework

Base Classifier and Generator

- Encoder-Predictor and Generator



Generative Explanation Framework

Base Classifier and Generator

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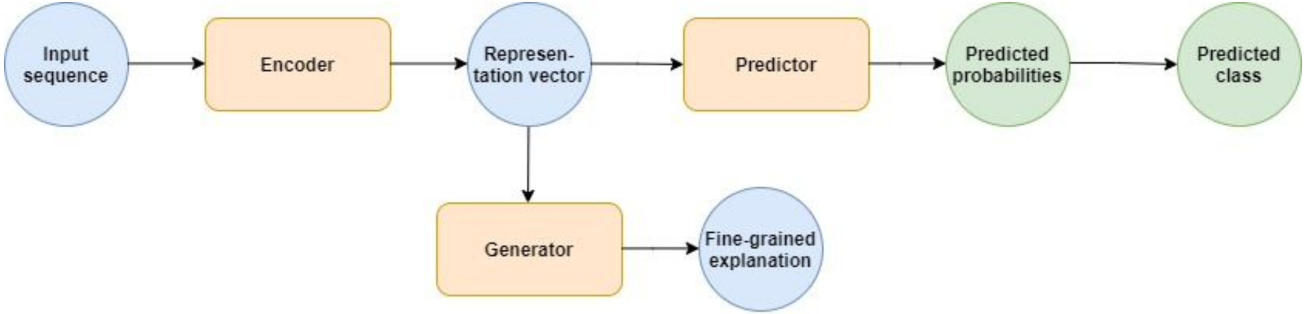

Generative explanations seem to be independent of the predicted overall results

Generative Explanation Framework

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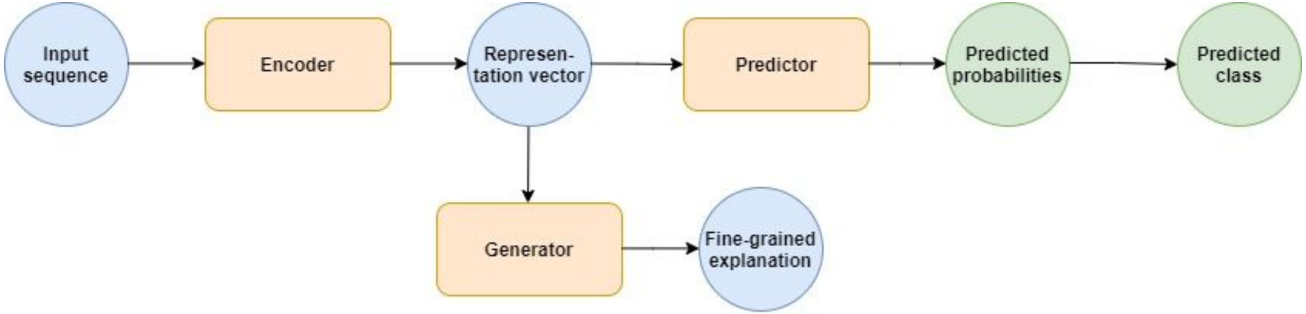

Generative explanations seem to be independent of the predicted overall results

Use Explanation Factor!

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Generative Explanation Framework

Explanation Factor

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- **Example:**

  “The product is good to use” ⇒ Overall rating = 5? or =4??

Generative Explanation Framework

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Generative Explanation Framework

Explanation Factor

- **Idea:** Pre-train a classifier which learns to predict by directly taking the explanations as input

Generative Explanation Framework

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Generative Explanation Framework

Explanation Factor

- **Idea:** Pre-train a classifier which learns to predict by directly taking the explanations as input

- This should predict the overall results more accurately than the base model that takes raw text as the input

Generative Explanation Framework

Explanation Factor

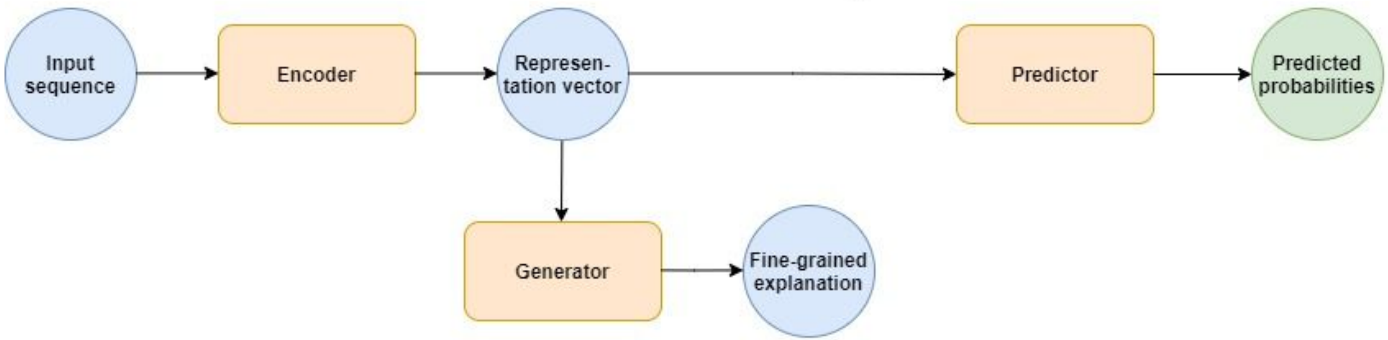
- **Idea:** Pre-train a classifier which learns to predict by directly taking the explanations as input

- The classifier also helps in providing a strong guidance for the text encoder to generate a more informative representation vector

Generative Explanation Framework

Explanation Factor

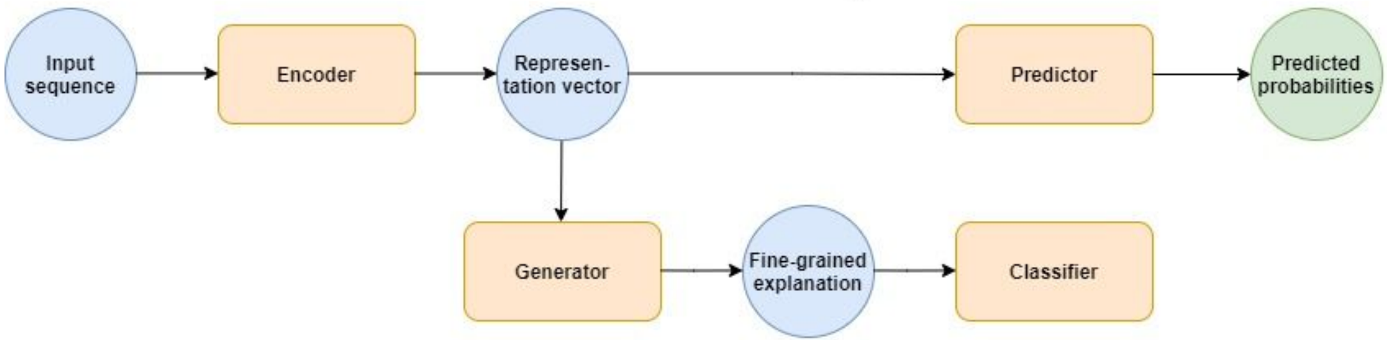
- Base classifier and Generator



Generative Explanation Framework

Explanation Factor

- (Pre-trained) Classifier



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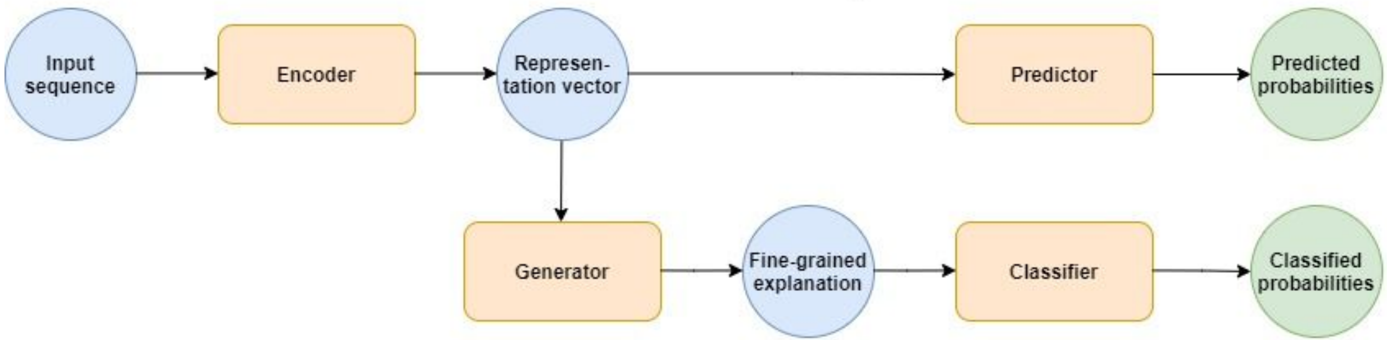
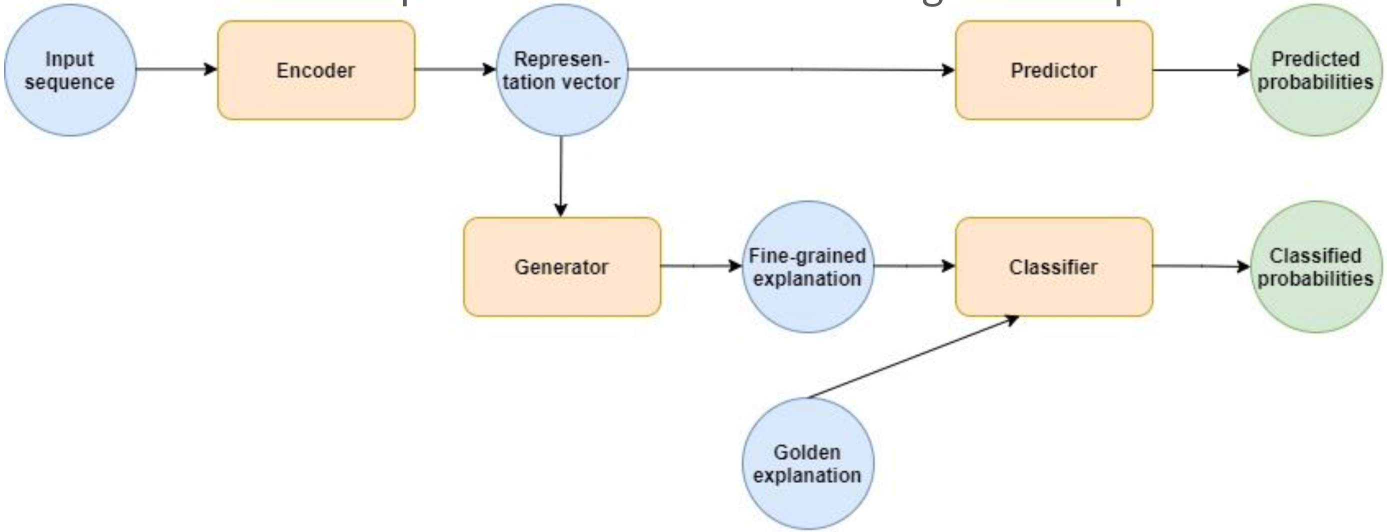


Generative Explanation Framework

Explanation Factor

- (Pre-trained) Classifier
  - Golden explanation ⇔ 'Actual' fine-grained explanation*



* the fine-grained information collected/scraped by the authors in this paper

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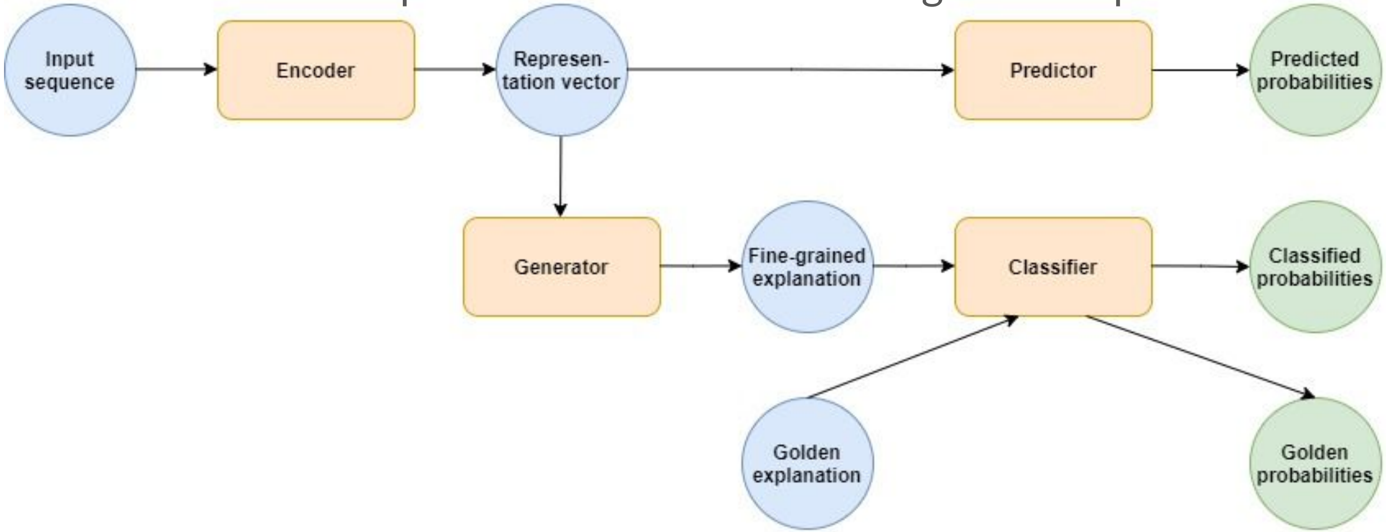

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Generative Explanation Framework

Explanation Factor

- Calculate **Explanation factor** from the obtained probabilities

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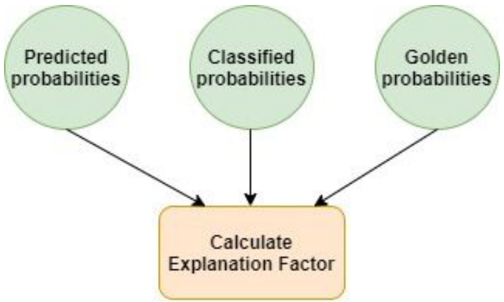

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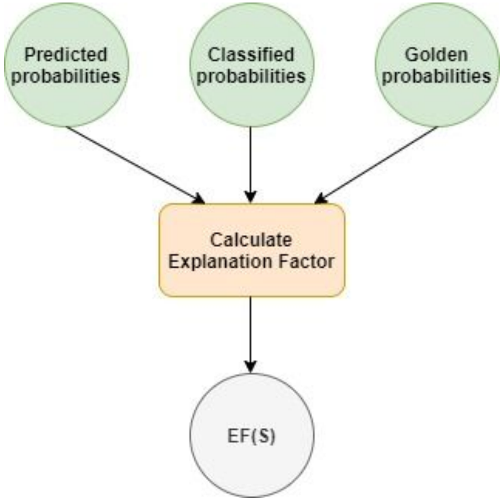

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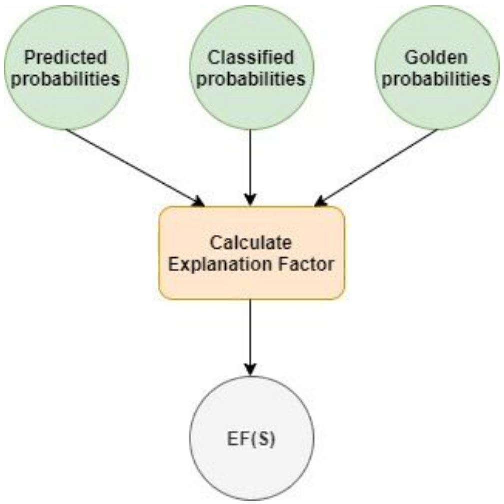

But how?

Generative Explanation Framework

Explanation Factor

1. Obtained probabilities:

$$P_{pred} = Predictor(v_e)$$

$$P_{classified} = softmax(f_C(W_C \cdot e_c + b_C))$$

$$P_{gold} = softmax(f_C(W_C \cdot e_g + b_C))$$

Generative Explanation Framework

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$$P_{classified} = softmax(f_C(W_C \cdot e_c + b_C))$$
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2. Extract ground-truth probability $\tilde{P}_{classified}, \tilde{P}_{pred}, \tilde{P}_{gold}$ from the obtained probabilities

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2. Extract ground-truth probability $\tilde{p}_{classified}, \tilde{p}_{pred}, \tilde{p}_{gold}$ from the obtained probabilities

Eg: $P_{classified}$ = [0.5 0.2 0.1 0.2] ; when $y = 2$ ⇒ $\tilde{p}_{classified}$ = 0.2

Generative Explanation Framework

Explanation Factor

3. Explanation factor:

$$EF(S) = |\tilde{p}_{classified} - \tilde{p}_{gold}| + |\tilde{p}_{classified} - \tilde{p}_{pred}|$$

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- $|\tilde{p}_{classified} - \tilde{p}_{gold}|$ $\rightarrow$ distance between the generated explanations and the golden explanations

Generative Explanation Framework

Explanation Factor

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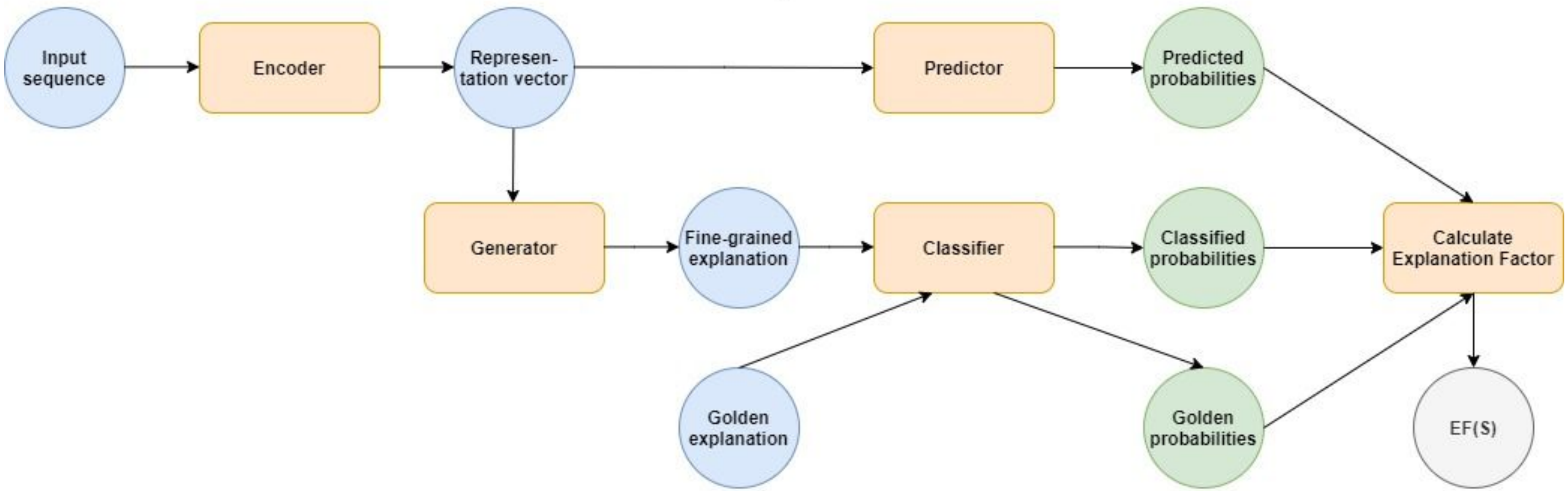
$$EF(S) = |\tilde{p}_{classified} - \tilde{p}_{gold}| + |\tilde{p}_{classified} - \tilde{p}_{pred}|$$

- $|\tilde{p}_{classified} - \tilde{p}_{gold}|$ $\rightarrow$ distance between the generated explanations and the golden explanations
- $|\tilde{p}_{classified} - \tilde{p}_{pred}|$ $\rightarrow$ relevance between the generated explanations and the original text

Generative Explanation Framework

Explanation Factor

- The GEF framework



Generative Explanation Framework

Algorithm so far...

- **Step -1 to 3:** Encoder, Predictor, Generator

Generative Explanation Framework

Algorithm so far...

- **Step -1 to 3:** Encoder, Predictor, Generator

- **Step -4:** Feed the generated fine-grained explanations to the pre-trained* classifier to obtain $P_{classified}$

*the pre-trained classifier is trained to output the right class as output using the golden explanations as input

Generative Explanation Framework

Algorithm so far...

- **Steps -1 to 3:** Encoder, Predictor, Generator

- **Step -4:** Feed the generated fine-grained explanations to the pre-trained* classifier to obtain $P_{classified}$

- **Step -5:** Feed the golden explanations to the pre-trained* classifier to obtain P_{gold}

*the pre-trained classifier is trained to output the right class as output using the golden explanations as input

Generative Explanation Framework

Algorithm so far...

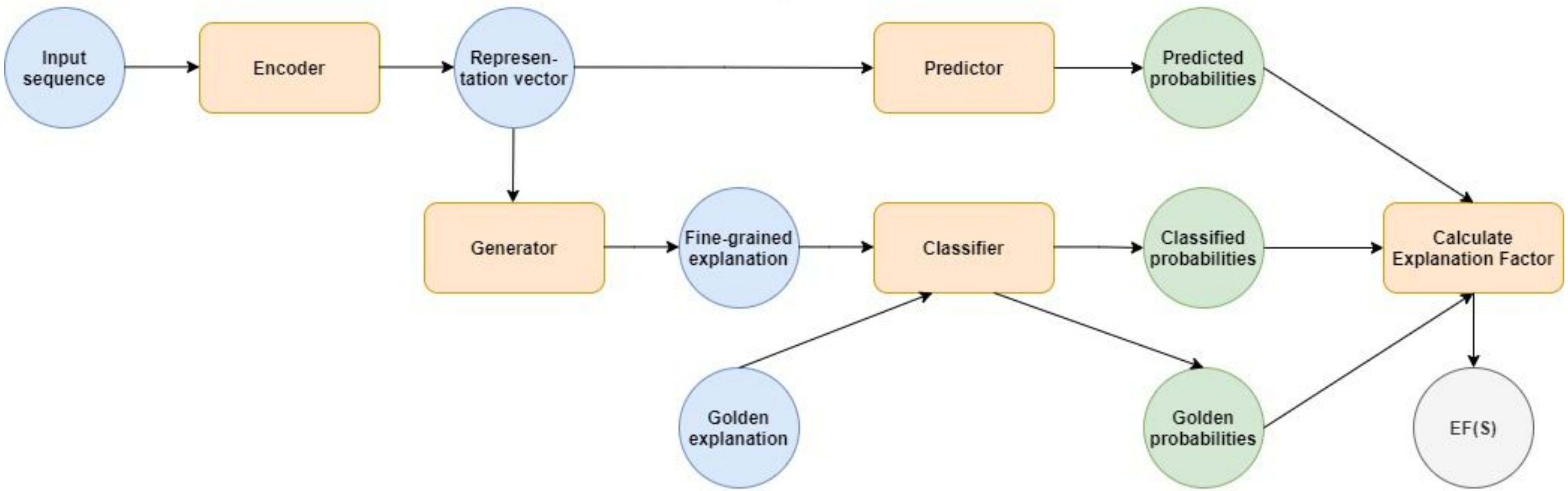
- **Step -6:** Calculate explanation factor from the obtained probabilities

$$EF(S) = |\tilde{p}_{classified} - \tilde{p}_{gold}| + |\tilde{p}_{classified} - \tilde{p}_{pred}|$$

Generative Explanation Framework

Explanation Factor

- The GEF framework



Generative Explanation Framework

Explanation Factor

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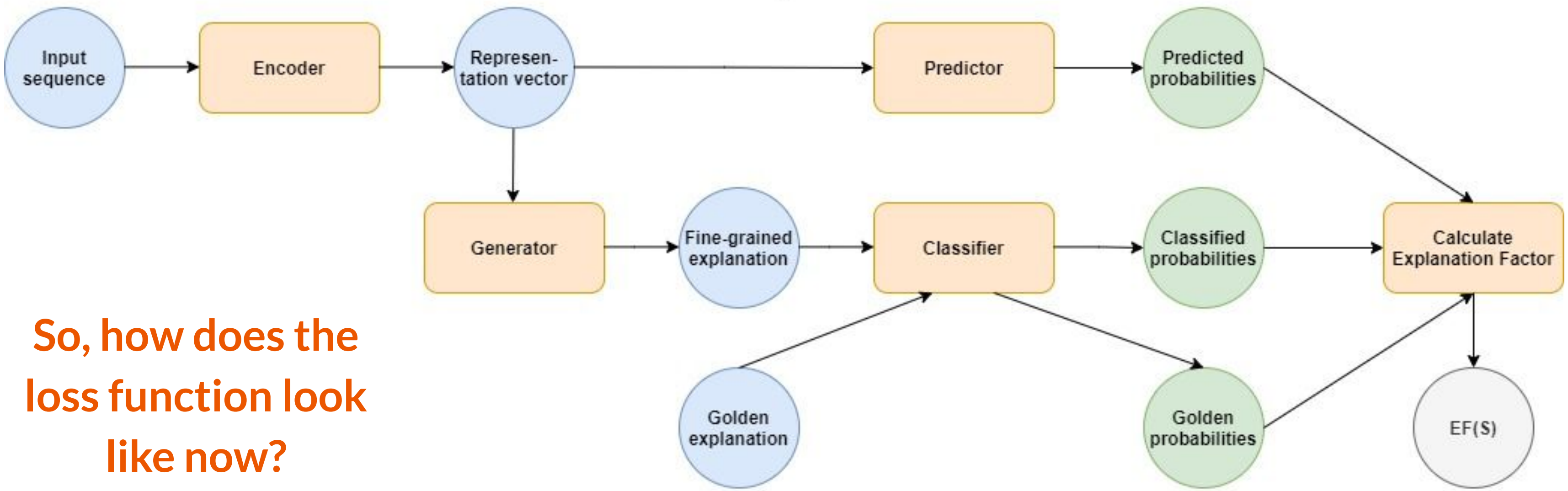

So, how does the loss function look like now?

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Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)
  - Minimize the expected loss i.e., risk over the training data

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)
  - Minimize the expected loss i.e., risk over the training data

$$\mathcal{L}_{MRT}(e_g, S, \theta) = \sum_{(e_g, S) \in D} \mathcal{L}(e_g, S, \theta) EF(S)$$

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)

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Generative Explanation Framework

Minimum Risk Training

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  - $\mathcal{L}(e_g, S, \theta)$ - Classification loss + Explanation generation loss

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)

$$\mathcal{L}_{MRT}(e_g, S, \theta) = \sum_{(e_g, S) \in D} \mathcal{L}(e_g, S, \theta) EF(S)$$

  - $\mathcal{L}(e_g, S, \theta)$ - Classification loss + Explanation generation loss
  - EF(S) is treated as the semantic distance of input texts, generated explanations and golden explanations

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)

$$\mathcal{L}_{MRT}(e_g, S, \theta) = \sum_{(e_g, S) \in D} \mathcal{L}(e_g, S, \theta) EF(S)$$

  - $\mathcal{L}_{MRT}$ can be zero or close to zero when $\tilde{p}_{classified}, \tilde{p}_{pred}, \tilde{p}_{gold}$ are close

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)

$$\mathcal{L}_{MRT}(e_g, S, \theta) = \sum_{(e_g,S)\in D} \mathcal{L}(e_g, S, \theta) EF(S)$$

  - $\mathcal{L}_{MRT}$ can be zero or close to zero when $\tilde{p}_{classified}, \tilde{p}_{pred}, \tilde{p}_{gold}$ are close
  - But, this cannot guarantee that generated explanations are close to the golden explanations

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)
    - To avoid total degradation of loss, the final loss function will be:

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)
  - To avoid total degradation of loss, the final loss function will be:

$$\mathcal{L}_{final} = \sum_{(e_g,S)\in D} \mathcal{L} + \mathcal{L}_{MRT}$$

Generative Explanation Framework

Minimum Risk Training

- Optimization: Minimum Risk Training (**MRT**)
  - To avoid total degradation of loss, the final loss function will be:

$$\mathcal{L}_{final} = \sum_{(e_g, S) \in D} \mathcal{L} + \mathcal{L}_{MRT}$$

  - Final loss function = Explanation generation loss + MRT loss

Generative Explanation Framework

Minimum Risk Training

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  - To avoid total degradation of loss, the final loss function will be:

$$\boxed{\mathcal{L}_{final} = \sum_{(e_g,S)\in D} \mathcal{L} + \mathcal{L}_{MRT}}$$

  - Final loss function = Explanation generation loss + MRT loss

Generative Explanation Framework

THE algorithm

- **Steps - 1 to 3:** Encoder, Predictor, Generator
- **Steps - 4 to 6:** Obtain the probabilities and calculate Explanation Factor
- **Step - 7:** Calculate the final loss and optimize the model

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Experiment results

- Fine-grained explanations are in different forms
  - Text
  - Numeric

Experiment results

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  - Text - PCMag review dataset
  - Numeric - Skytrax airline review

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- GEF has been applied to both forms of explanations using different base models

Experiment results

- Fine-grained explanations are in different forms
  - Text - PCMag review dataset
  - Numeric - Skytrax airline review
- GEF has been applied to both forms of explanations using different base models
- Experimental settings are set the same for base model and base model+GEF for easy comparison of the performance

Experiment results

Experimental settings

- **Tokenizer** : Stanford Tokenizer
- **Embedding** : GloVe
- **Optimizer** : Adam
- **Stopping criteria** : Stop updating when the classification loss reaches a certain threshold [since generation loss > classification loss for text explanations]

Experiment results

Text explanations

- PCMag dataset:
  - Long review text for electronic products
  - Three short comments
    - positive, negative, neutral
  - Overall rating score
    - {1.0, 1.5, 2.0, ..., 5.0}
- Filter: review text with >70 sentences or comments >75 tokens have been removed
- Train/Dev/Test: 10919/1373/1356

Experiment results

Text explanations

- **Base model**: CVAE [Conditional Variational AutoEncoder]
- **Proposed model**: CVAE + GEF
- **Classifier:** Skip-connected model with bidirectional GRU-RNN layers
- **Evaluation metric (for text generation):** BLEU score
- **Evaluation metric (for classification):** top-1, top-3 accuracy

Experiment results

Text explanations

		BLEU-1	BLEU-2	BLEU-3	BLEU-4
Pos.	CVAE	36.1	13.5	3.7	2.2
	CVAE+GEF	**40.1**	**15.6**	**4.5**	**2.6**
Neg.	CVAE	33.3	14.1	3.1	2.2
	CVAE+GEF	**35.9**	**16.0**	**4.0**	**2.9**
Neu.	CVAE	30.0	8.8	2.0	1.2
	CVAE+GEF	**33.2**	**10.2**	**2.5**	**1.5**

Table 4: BLEU scores for generated explanations.

- **Base model**: CVAE [Conditional Variational AutoEncoder]
- **Proposed model**: CVAE + GEF
- **Classifier:** Skip-connected model with bidirectional GRU-RNN layers
- **Evaluation metric** **(for text generation):** BLEU score
- **Evaluation metric** **(for classification):** top-1, top-3 accuracy

Experiment results

Text explanations

	Acc% (Dev)	Acc% (Test)
CVAE	42.07	42.58
CVAE+GEF	**44.04**	**43.67**
Oracle	46.43	46.73

Table 5: Classification accuracy on PCMag Review Dataset. *Oracle* means if we feed ground-truth text explanations to the Classifier C, the accuracy C can achieve to do classification. *Oracle* confirms our assumption that explanations can do better in classification than the original text.

- **Base model**: CVAE [Conditional Variational AutoEncoder]
- **Proposed model**: CVAE + GEF
- **Classifier:** Skip-connected model with bidirectional GRU-RNN layers
- **Evaluation metric** **(for text generation)**: BLEU score
- **Evaluation metric** **(for classification)**: top-1, top-3 accuracy

Experiment results

Numerical explanations

- Skytrax dataset:
  - Review text of airlines
  - Five sub-field scores - [0-5]
    - Seat comfortability, cabin stuff, food, in-flight environment, ticket value
  - Overall rating score - [1-10]
- Filter: review text with >300 tokens
- Train/Dev/Test: 21676/2710/2709

Experiment results

Numerical explanations

- **Base model:** LSTM and CNN
- **Proposed model:** LSTM + GEF
  CNN + GEF
- **Evaluation metric:** Accuracy

Experiment results

Numerical explanations

	s%	c%	f%	i%	t%
LSTM	46.59	52.27	43.74	41.82	45.04
LSTM+GEF	**49.13**	**53.16**	**46.29**	**42.34**	**48.25**
CNN	46.22	51.83	44.59	43.34	46.88
CNN+GEF	**49.80**	**52.49**	**48.03**	**44.67**	**48.76**

Table 6: Accuracy of sub-field numerical explanations on Skytrax User Reviews Dataset. s, c, f, t, v stand for seat comfortability, cabin stuff, food, in-flight environment and ticket value, respectively.

- **Base model:** LSTM and CNN
- **Proposed model:** LSTM + GEF

  CNN + GEF
- **Evaluation metric**: Accuracy

Experiment results

Numerical explanations

	Acc%	Top-3 Acc%
LSTM	38.06	76.89
LSTM+GEF	**39.20**	**77.96**
CNN	37.06	76.85
CNN+GEF	**39.02**	**79.07**
Oracle	45.00	83.13

Table 7: Classification accuracy on Skytrax User Reviews Dataset. *Oracle* means if we feed ground-truth numerical explanation to the Classifier C, the accuracy C can achieve to do classification.

- **Base model:** LSTM and CNN
- **Proposed model:** LSTM + GEF

  CNN + GEF
- **Evaluation metric:** Accuracy

Experiment results

Human evaluation

	Win%	Lose%	Tie%
CVAE+GEF	51.37	42.38	6.25

Table 8: Results of human evaluation. Tests are conducted between the text explanations generated by basic CVAE and CVAE+GEF.

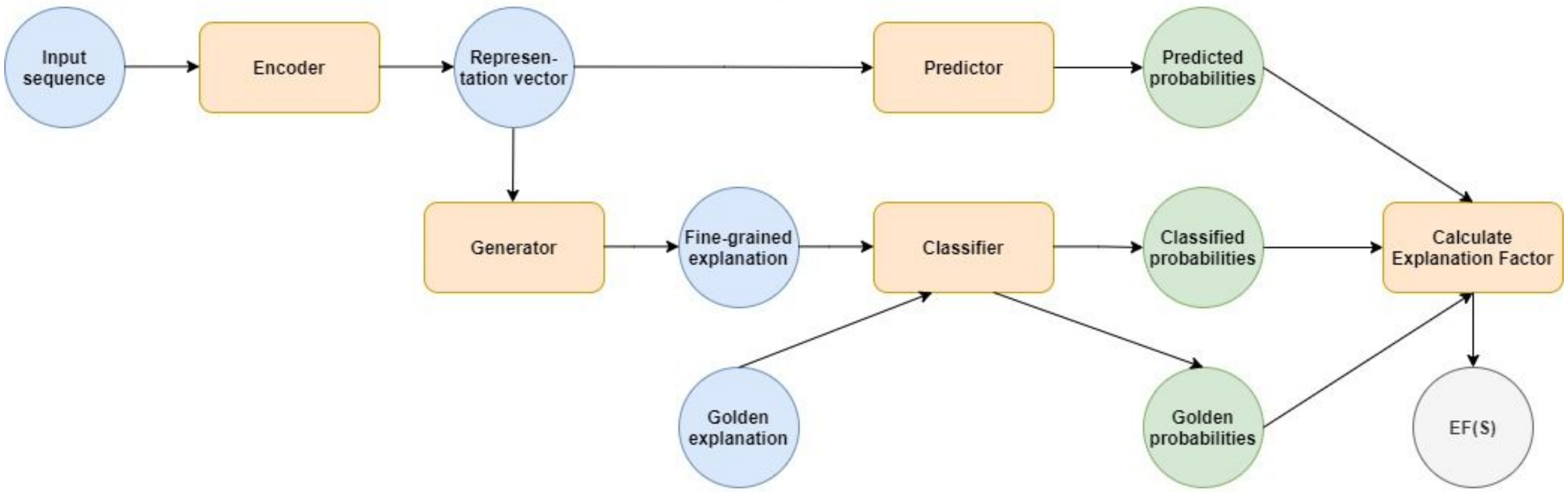
- Crowdsourced judges in Amazon Mechanical Turk
- **# samples** : 100 items
- **# judges** : 5
- All items are correctly classified using both basic model and using GEF

Summary

- Rationale is essential for an NLP system to be reliable
- A novel Generative Explanation Framework is introduced
- GEF uses the generated fine-grained information to leverage the performance of the text classification model

Summary

- The GEF framework



The End